THE IMPACT OF PUBLIC INFORMATION ON BIDDING IN HIGHWAY PROCUREMENT AUCTIONS

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November 2005

ABSTRACT:

A number of papers in the theoretical auction literature show that the release of information regarding the seller's valuation of an item can cause bidders to bid more aggressively. This widely accepted result in auction theory remains largely untested in the empirical literature. Recent theoretical work has also shown that this effect can be more pronounced in auctions with larger common cost uncertainty. We examine the impact of a policy change by the Oklahoma Department of Transportation that led to the release of the state's internal estimate of the costs to complete highway construction projects. We perform a differences-in-differences analysis comparing bidding in Texas, a state that had a uniform policy of revealing the same information all throughout the period of analysis, to bidding in Oklahoma. Our results show that, in comparison to Texas auctions, the average bid in Oklahoma fell after the change in engineers' cost estimate (ECE) policy. This decline in bids was even larger for projects where the common uncertainty in costs is greater. Moreover, the within-auction standard deviation of bids fell after the change in ECE policy with the most significant decline observed again in projects with greater common cost uncertainty.

JEL classifications: D44 (Auctions); H57 (Procurement)

Keywords: Information release, procurement auctions

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**The authors would like to thank George Deltas, Ken Troske, conference participants at INFORMS 2005, and seminar participants at Texas Tech University and the University of Oklahoma for valuable comments. We are indebted to staff at the ODOT and TXDOT for useful information.

I. INTRODUCTION

A fundamental result from auction theory is that the public release of information regarding the valuation of an object can lead to more aggressive bidding behavior (see Milgrom and Weber (1982), Harstad (1990), and Campbell and Levin (2000)). In a competitive environment, the release of information can intensify competition among bidders by making values more predictable. This effect is pronounced in auctions of objects with common value uncertainty (Goeree and Offerman (2003)). Public information can also lower the relative value of a bidder's own private information thus reducing his rents. These predictions are widely accepted but remain largely untested using field auction data. For the most part, the empirical evidence on the impact of public information dissemination is confined to laboratory experiments (see Kagel, Harstad and Levin (1987), Goeree and Offerman (2002), and Kagel, Levin and Harstad (1995)).[1]

This study examines the role of information release on bidding behavior using data from highway construction procurement auctions. Each state in the US conducts transportation procurement auctions and billions of dollars of construction projects are awarded annually through this process. The auctions are first-price sealed bid auctions and are held in each state at regular intervals throughout the year. While the auction format is quite similar in most states, a feature that varies across states is the information provided to bidders regarding the state's internal estimate of the cost of a project.[2] Some states release this information prior to bidding and others do not. Oklahoma recently changed its policy in this regard. Prior to the change in policy, it was illegal for state officials to disclose the state's cost estimate before bids were opened. During a six month period beginning at the end of 1999, the Oklahoma Legislature initiated a set of changes to state laws that overturned this policy. Bidders now have access to the state's cost estimate prior to bid submission. This change in Oklahoma's information policy is

[1] The results from experiments performed in Kagel, Harstad and Levin (1987) and Goeree and Offerman (2002) agree with the predictions of Milgrom and Weber (1982). Alternatively, Kagel, Levin and Harstad (1995) show that in some experiments when the bidders' behavior is out of the equilibrium path such policy prescriptions fail.

[2] This is called the engineers' cost estimate and is used as a benchmark to judge the submitted bids. For example, in Oklahoma, the state uses the engineers' cost estimate to establish a reserve value for a project and if the low bid is seven percent above the engineers' cost estimate, the state may reject the low bid and re-auction the project off at a later time.

similar, in spirit, to the information release discussed in Milgrom and Weber (1982) and this information policy change forms the basis of our test of the theory.

As mentioned above, the existing evidence on the effect of public information release in auctions is quite limited and is mostly coming from experiments. The empirical literature's closest evidence is of simulations of a public information disclosure. In a study of open auctions of apartments in Sweden, Eklof and Lunander (2003) estimate the distribution of private values when the reserve prices are secret. They then simulate the effect of moving to an open reserve price mechanism and find that the seller's revenue would be about 10% higher if the reserve price was announced. The empirical studies of drainage auctions examine how asymmetries in the precision of the bidders' information affect their bidding behavior (see Hendricks and Porter (1988) and Hendricks, Porter, and Wilson (1994)). The focus is generally placed on studying the magnitude of information rents in asymmetric environments when one bidder can acquire better information than others (see Hendricks, Porter, and Boudreau (1987) and Porter (1995)).[3] In wildcat auctions where information is relatively symmetric, there is some evidence that royalty schemes that provide revenue insurance increase bids. In Treasury bill auctions, Nyborg, Rydquist and Sundaresan (2002) show that increased market volatility can lead to lower demand, lower prices and increased dispersion of bids. Part of this behavior is due to risk aversion. In a study of computer auctions on Ebay, Yin (2005) examines the effect of value dispersion and seller reputation on prices. She finds that the seller's reputation complements information provided by the auction site by lending more credibility to it. However, none of these empirical papers provides a direct test of Milgrom and Weber's hypothesis that the provision of public information regarding the valuation of an item affects bidding behavior.

To this end, we empirically examine the impact of the release of public information in Oklahoma auctions using a differences-in-differences approach and compare the changes in bidding behavior in auctions held in Oklahoma and Texas. Texas had a uniform

[3] Athey and Levin (2001) provide another example of an asymmetric environment in timber auctions. They show how bidders strategically use their private information in bidding. A recent theoretical study by Mares and Harstad (2003) relates the two strands of literature by examining the benefits of private information disclosure to a subset of bidders and compares those to the benefits of public disclosure of information.

information release policy throughout the entire period and we use the Texas auctions as a control group. The data include over 13,000 submitted bids by construction firms in Oklahoma and Texas over the period 1998-2003. Our empirical analysis provides evidence in support of the theory; the average level of bids is lower after the release of additional information. Despite the competitive pressure created by the information release, the lower average bids do not result in statistically significant lower winning bids.

The theory suggests that the effects of information release should be more apparent in auctions with a greater degree of common cost uncertainty. Within the set of auctions used in this analysis, we isolate two types of projects that appear to differ significantly in the level of common cost uncertainty associated with the specific construction tasks. The two project types are asphalt paving projects and bridge construction/repair work. We argue that in asphalt projects one has to rely more on the individual firm's state of equipment and internal efficiency to determine the cost, while in bridgework projects there is more uncertainty that is common to all bidders.[4] We find, in agreement with the theory, that the effect of information release is stronger for bridgework projects. To our knowledge, this is the first paper that studies and compares the impact of a public information release among auctions with different degrees of common cost uncertainty.

The remainder of the paper is organized as follows. Section II describes the bidding process and presents the theoretical framework. Section III provides a description of the data while Sections IV and V report the results. In Section VI, we offer some concluding comments.

II. Information Policy & Auctions

Oklahoma ECE Policy Change

Before November 1999, the law in Oklahoma explicitly prohibited the release of the state's engineers' cost estimate (ECE) prior to bid letting. In fact, very few people within

[4] We discuss below the differences in the uncertainty of costs associated with asphalt and bridge work. In short, asphalt paving projects are relatively straightforward as the job descriptions typically specify an area of roadwork to be surfaced, a depth of surfacing required, and the material to be used in the surfacing project. In bridgework, there is more uncertainty. Soil conditions at a site may not be fully known until excavation work begins and repairs may not be fully understood until some demolition work is undertaken.

the Department of Transportation (DOT) were entrusted with this information and it was a felony offense to release the estimate. In November 1999, the law was changed. The Oklahoma statute (OS 61, section 116) was amended to include the phrase "The public agency's engineering estimate of the actual cost of the project shall not be considered confidential and shall be open for public inspection." Bidders could now request access to the ECE prior to bid letting. In April 2000, the legislature amended the section further to state that the ECE "shall be available to the public in accordance to the Oklahoma Open Records Act." This change allowed the full release of the details of the ECE to all potential bidders.

Table 1 shows the current ECE release policy for individual states. Only eight states release the actual estimates, either with their advertisement of the projects or upon request. Five states provide a total "budgeted" amount that may include costs that are not part of the bid amount. Fourteen states release a range of possible costs instead of the actual estimate. Twenty-three states do not release the engineering estimate before the bid letting. Of those, eight do not release it even after the bids are opened.

Oklahoma is not the only state that has enacted changes in ECE policy. There have been recent shifts in ECE policy in Florida, New Hampshire, North Carolina, Utah and Illinois. Prior to these recent changes, Florida and New Hampshire did not provide any estimates of the ECE before or after bid letting, and North Carolina and Utah released the ECE only after bids were opened. Currently, New Hampshire and Utah release the ECE prior to bidding (as in Oklahoma) and Florida and North Carolina provide a budgeted amount that is based on the ECE prior to bid letting. Alternatively, Illinois changed its policy in the opposite direction, restricting access to the ECE, and state authorities in Michigan are also considering a similar policy change.

INFORMATION RELEASE AND AUCTION THEORY

In first-price sealed bid auctions with affiliated values, Milgrom and Weber (1982) have shown that the release of public information induces more competitive bidding and may result in higher revenues. In theorem 16, they state that "In a first price auction a policy of publicly revealing the seller's information cannot lower and may raise the expected price."[5] In a competitive environment, the release of information can have two

[5] See also Theorem 5.4.18 in Milgrom (2004).

effects on bidding behavior. First, it can reduce the impact of the bidder's own private information on his estimate of the value and, as a result, reduce his information rents. Second, it can make values more predictable thus encouraging more intense competition from all bidders.

To formalize the role of public information in auctions, we present a simple model of competitive bidding with additive and separable common and private cost components. This model, first introduced by Goeree and Offerman (2003), provides useful directions for the empirical analysis that follows. The framework produces a simple bidding function with the added advantage that it allows us to assess the relative magnitude of the impact of an information release when the size of the common cost component relative to the private cost component changes. We can also provide an explanation for the observed difference in the impact that the release of information has on projects with predominantly private costs (such as asphalt), and projects with predominantly common costs (such as bridgework). Finally, due to its simplicity, the framework can predict effects on the variance of bids.

There are $n \geq 2$ risk neutral bidders who compete for a government contract in a first price sealed bid auction. The cost of the contract to a bidder, i, consists of two components: the private cost component c_i and the common cost component V. Each one of the n bidders has an unbiased estimate, v_i, of the true common cost. The common cost component is modeled here as the average of the bidders' estimates, i.e., $V = \sum_{i=1}^{n} v_i / n.$[6] The private and common cost estimates are identically and independently distributed across bidders. The density of the private cost c_i to bidder i is f_c that is strictly positive on the support $[c_L, c_H]$. Similarly, the density of the common cost component is f_v and it is strictly positive on its support $[v_L, v_H]$. We assume that the densities f_c and f_v are logconcave.[7]

[6] This modeling framework has been previously used in many theoretical papers such as Albers and Harstad (1991), Bikhchandani and Riley (1991), Vincent (1995), Klemperer (1998), Bulow, Huang, and Klemperer (1999), and Goeree and Offerman (2003). Alternatively, in the more traditional formulation adopted by Wilson (1969), bidders draw their signals from a known distribution conditional on the realization of V. These two formulations have the same qualitative features (see also the discussion in Goeree and Offerman (2003) and Milgrom (2004)).

[7] The assumption of logconcavity is discussed in detail in Goeree and Offerman (2003). It guarantees that a lower privately observed cost implies, on average, a lower overall cost thus ensuring monotonicity and existence.

In this environment, a bidder who is awarded a contract at a bid of b_i receives a net profit of $b_i – c_i – V$. The following strategy is the unique symmetric equilibrium bidding strategy for bidder i in the first price auction:

$$B(s_i) = \frac{n-1}{n} E[v \mid s \geq s_i] + E[y_1 \mid y_1 \geq s_i] \tag{1}$$

where $s_i = v_i / n + c_i$ is i's privately observed component of the cost and y_1 is the lowest value of the remaining n-1 estimates of s. This function is derived in appendix A. An alternative way to express this bidding function for any estimate x of the privately observed component of the cost is:

$$B(x) = E[V + c \mid s_i = x, Y_1 = x] + E[y_1 - Y_1 \mid s_i = x, Y_1 = x] \tag{2}$$

where Y_1 is the lowest estimate of s among all bidders. The first term of this expression represents the bidder's estimate of the expected value of the total cost, and the second term is the potential information rent of the bidder. As a result, each bid is an estimate of the entire cost increased by the private information rent.

The seller can also obtain an estimate of the common cost V. If he decides to obtain and release that estimate to the bidders, the value of n increases by one and the weight placed upon any privately observed signal becomes lower, $s_i = v_i / (n+1) + c_i$. As a result, the private information rents are reduced and bidders bid relatively more aggressively. The larger the relative size of the common cost component, the more aggressive the bidding behavior is expected to be after the information is released. If the seller's estimate carried a larger weight than any other estimate, his decision to acquire and release it to bidders would reduce the private information rents even more leading to lower bids on average. With the release of that information all bidders get to learn the state's estimated value of the common cost.[8] Bids become more concentrated as the information rents are reduced at every level of bid.

[8] Indeed, according to a discussion with a state official the engineering estimate obtained by the state is not unveiling the true common cost but is rather another estimate that involves some amount of uncertainty as well. This is a feature that we were hoping to capture in our modeling effort.

To recap, the release of information is likely to induce aggressive bidding behavior. The larger the common value component of the cost, the lower the bids and the lower the variance of bids is expected to be after the information is released. On the other hand, if the costs were purely private, in a competitive environment, the release of information would have no effect on the bids. Our empirical analysis will perform three tests of this theory. First, we will estimate the overall effect of the change in ECE policy on bids and winning bids. Second, we will estimate the effects of the change in ECE policy on projects with differing levels of common and private cost components. We expect that the change in ECE policy will more greatly affect the bidding in project types with larger common cost components. Third, we model the variance of bids as a function of the change in policy. We expect variances to decline after the change in ECE policy.

Throughout this discussion, it is assumed that the competitive environment is maintained. One concern raised by transportation officials is that the release of the ECE may result in less competitive bidding environments. Clearly, collusion has been a problem in this industry in the past (Porter and Zona (1993)) and the federal government has put together guidelines for the detection and prevention of collusive behavior. With regard to the state's ECE, the guidelines recommend that states not make the information available prior to the award of the contract. The rationale for this recommendation is that the release of the ECE may "encourage and facilitate bid rigging."[9] If such a change in competitive environment occurred due to the change in ECE policy, then this would weaken our test of the theoretical predictions. To be sure, we know of no prosecution of bid rigging in the Oklahoma Department of Transportation (ODOT) auctions during the time period under analysis.

III. DATA AND MEASUREMENT ISSUES

This study employs data obtained from the Oklahoma and Texas (TXDOT) Departments of Transportation on auctions of construction projects for the period

[9] This recommendation and rationale are discussed in *Suggestions for the Detection and Prevention of Construction Bid Rigging* (1983) authored by the US Department of Transportation and the US Department of Justice (see http://www.fhwa.dot.gov/programadmin/contracts/dotjbid.htm.).

between January 1998 and August 2003.[10] The data include auctions from the entire state of Oklahoma and from the North Texas and Panhandle construction districts in Texas. These areas of Texas border on Oklahoma, have similar topography and soil conditions, and use similar grades of construction materials as those in Oklahoma.[11] For each project auctioned off, we know the contractors that purchased plans (plan holders), the bids submitted by each contractor if they bid, the winning bidder, and the winning bid. In addition, both states provide data describing each project. The data give the location, a detailed description of the tasks, the estimated time to completion and, most importantly, the ECE for each project. With this information, we construct a panel data set on bidders where an observation in our data set represents a plan held and possibly a bid submitted by a bidder for a given project. Bidders may place multiple individual bids in a month or may elect not to bid at all in some months; hence, the panel structure is quite unbalanced.

The top two panels of Table 2 provide a summary of the auction data for Texas and Oklahoma broken out by the ECE policy information periods described above–January 1998-October 1999, November 1999-March 2000, and April 2000-August 2003. The table includes statistics on the number of auctions, bidders, and values of bids submitted. The information on bids is presented as the relative bid which is measured as the bid divided by the engineering cost estimate.[12] This allows for a direct comparison of bids across projects of different sizes. Three points are worth noting. First, the sample is relatively balanced between Oklahoma and Texas with slightly fewer auctions in Texas compared to Oklahoma in each of the three periods. Second, participation levels, both in terms of the number of plan holders and the number of bidders, are generally higher in Texas compared with Oklahoma. On average, the number of bidders in Texas exceeds that in Oklahoma by .5 to 1.0 bidders per auction. Third, it appears that, in both

[10] The Oklahoma dataset is obtained from three reports in the ODOT website, namely the as read bid report, the low bid report, and the award notice. The Texas data are provided by the TXDOT. We use the 1997 data to initialize variables on bidding history and capacity utilization that are discussed more fully below.

[11] We use all well-defined project types (i.e., asphalt, concrete, bridge, traffic signal, grade and drainage/grading projects) in both states but exclude miscellaneous projects. Miscellaneous projects are typically smaller projects that may involve such tasks as mowing, painting, sign replacement, and construction at rest stops.

[12] Bajari and Ye (2003) also analyze highway procurement auctions focusing on the relative bids as their measure of bids in an auction. Alternatively, some studies use the log of the bids in their study. We estimate our models both ways but report mainly the relative bid results. With regard to ECE policy variables, the relative bid and log of the bids models give qualitatively similar results across our different specifications.

Oklahoma and Texas, relative bids and relative winning bids have declined over time but the decline is more marked in Oklahoma. This last point is reflected in Figures 1 and 2. Figure 1 presents the kernel density plots for the relative bid distributions for the three ECE periods for Oklahoma, and Figure 2 shows the same set of distributions for Texas. In Oklahoma, the leftward shift of the distribution is considerably more pronounced.

IV. EMPIRICAL MODEL AND RESULTS

Our first test of the effect of the change in information release policy in Oklahoma will take a panel-data differences-in-differences approach. We will compare the changes in bidding behavior in Oklahoma and Texas. In Texas, there was no change in policy with the ECE being available to bidders prior to bid letting for the entire sample. In Oklahoma, there was a distinct change in the policy as described above. We will model this change in information by classifying our auctions into three distinct time periods– pre-November 1999, November 1999-March 2000, and post-March 2000. In the first period, the ECE for Oklahoma projects is not known prior to the bid letting. The second time interval is a period of transition and encompasses the two changes in legislation that occurred in November of 1999 and March of 2000. In the final time period, the ECE is available to bidders and both legislative changes have been enacted. We will estimate a differences-in-differences model that allows for differential effects across the three time periods. Our basic econometric specification is given below as

$$rbid_{iat} = \alpha_i + \beta_1 D_t^{OK} + \beta_2 D_t^{TR} + \beta_3 D_t^{OK,TR} + \beta_4 D_t^{AF} + \beta_5 D_t^{OK,AF} + X\Gamma + \varepsilon_{iat} \qquad (3)$$

where the unit of observation is firm *i* bidding in auction *a* in time period *t*. The dependent variable is the relative bid defined above and the β's measure the change in bidding that occurs between Texas and Oklahoma across the three ECE policy periods. The coefficient on D_t^{OK}, β_1, measures the average difference in bidding between Oklahoma and Texas auctions. The coefficients, β_2 and β_4, capture the average difference in bidding in auctions during the transition period and after the ECE policy change period, respectively. β_3 measures the difference in bidding that occurs in Oklahoma auctions compared to Texas auctions during the transition period and β_5 measures the difference in bidding that occurs in Oklahoma auctions compared to Texas auctions in the period after the ECE policy-change. Our main interest is on the coefficient β_5. If the theory is applicable to these data, we expect that β_5 should be negative. β_3 is more difficult to make predictions about since the ECE policy changes are not fully enacted until the end of the time period. In fact, the actual policies are in flux until the passage of the Opens Record Act provision. A crucial requirement is that we control for any additional factors that could differentially impact Oklahoma auctions compared to Texas auctions in the later periods in order to interpret β_5 as reflecting the change in ECE information policy. All models will include bidder fixed effects (α_i's) as well as a set of controls (**X**'s) for bidder, rival, auction, and business conditions variables.[13]

VARIABLE DEFINITIONS

The main dependent variable used throughout the analysis is the relative bid though we do present a number of specifications using the log of the bid as the dependent variable. The independent variables can be classified into five main groups–ECE information policy controls, auction characteristics, bidder characteristics, rival characteristics and business environment characteristics. Table B1 in appendix B provides a detailed definition for each of the variables used in the study. There are two auction-level variables – the number of bidders and a set of project type dummies. The number of bidders controls for differences in competition in auctions and the project type dummies control for the fact that we observe differences in bidding across project categories. We include two bidder characteristic variables, in addition to firm fixed effects, that measure the cost heterogeneity of bidders – the bidder's capacity utilization rate and the bidder's distance to a project. As a bidder's capacity utilization rises or as a bidder's distance to a project increases, we expect a bidder to submit higher bids. Three variables that measure rival characteristics are also constructed. First, we utilize past information on rivals' bidding success and construct the average winning percentage of

[13] Our models are estimated with firm fixed effects to control for bidder heterogeneity. A related model has been estimated in the literature using auction fixed effects but that is not possible here because the ECE policy control variables do not vary within auctions. To check how our data compare to other papers that estimate the reduced form bid model with auction fixed effects, we replicated the relative bid model reported in Bajari and Ye (2003). Our results are quite similar in spirit to Bajari and Ye (2003). Relative bids increase with a firm's distance to a project and decline when firms have more prior production experience and when rivals are close to the project. The one difference is that we did not find a statistically significant effect for a firm's capacity utilization on bids.

all rival plan holders in an auction. This is a measure of rival toughness. If firms face a set of tough rivals, we expect them to bid more aggressively. Second, we include the rivals' minimum distance to the project and the minimum backlog of the rivals. These variables are also used to control for rival cost heterogeneity and are similar to variables used by Bajari and Ye (2003).[14]

In the analysis that follows, it is important to control for factors that change over time other than the ECE information. Three variables are included that control for the business environment: (1) the monthly variation in the amount of projects being let, (2) the monthly unemployment rate, and (3) the monthly building permits. The first variable measures the real volume of projects auctioned off in each state in each month. The aggregate real volume of projects auctioned off in a month and in a state will vary due to budgetary conditions and seasonal factors. This may affect bidding behavior if firms bid more or less aggressively as the relative real volume of projects being let changes. The time-series plot of the quarterly series for both Texas and Oklahoma is shown in Figure 3. The graph shows that the real volume of projects in Oklahoma peaked in the middle part of our sample and has fallen off compared to Texas toward the latter half of 2002. Two additional variables are included to control for business conditions that vary over time and may affect bidding–the state unemployment rate and the state building permits. We expect that as unemployment or building permits change over time firms' non-state construction activity may fluctuate and this may affect bidding on state projects. Figure 4 shows how the unemployment rate varies over the sample period for Oklahoma and Texas. Oklahoma's unemployment rate is somewhat lower than Texas's unemployment rate but the time series patterns are quite similar across the two series. In the regression models, we include the three-month moving average for the permits and real volume of projects series along with the concurrent unemployment rate. Summary statistics of all the regression variables are presented in Table B2.

DIFFERENCES-IN-DIFFERENCES RESULTS

All the differences-in-differences models are estimated with firm fixed effects and include a set of monthly dummy variables along with the controls for bidder, rival,

[14] See also Jofre-Bonet and Pesendorfer (2000), De Silva, Dunne and Kosmopoulou (2003), and De Silva, Jeitschko and Kosmopoulou (2005).

business conditions and auction characteristics discussed above. The standard errors reported are cluster-robust standard errors where the clustering is on firms. We estimate the models on two samples of bids. One sample includes all bids submitted and our results will measure how changes in ECE policy influence overall bidding behavior. A second sample estimates the model using only winning bids and these runs will assess how the change in ECE policy relates to the winning bid. These latter regressions measure more directly the effect of the ECE policy change on Oklahoma's procurement costs.

Table 3 reports the results for our base model. The first column presents the coefficients for the base model using all relative bids and the second column presents the estimates from the sample restricted to the winning relative bids. The first set of coefficients in the table is the policy response controls. The key parameter of interest in this group is β_5 that measures the difference in bidding between Oklahoma and Texas auctions in the period after the ECE policy change (post-March 2000). Two clear patterns emerge. On average, bidding is lower in Oklahoma after the change in ECE policy by about 5.0 percent. With regard to the winning bids (column 2), there is no statistically significant effect of the change in ECE policy on the observed winning bids. Alternatively, in the transition period when ECE policies were being changed, there is no difference in bidding between Oklahoma and Texas. The last two columns report the results where the log of the bid is used as the dependent variable and the log of the ECE is used as a control variable. The findings are quite similar to the models estimated with the relative bid as dependent variable. The log of the bids is lower in period after ECE policy change though there is no effect on winning bids.

With regard to the other variables in the model, the number of bidders appears to have the most consistent impact. As the number of bidders increases, bidding becomes more aggressive and winning bids fall. Therefore, increased competition results in lower procurement costs for the states. If the winner has a higher capacity utilization rate, bids tend to be higher. The only rival variable that consistently matters is the average rival winning to plan holder ratio. As rivals get tougher, bids generally decline. The variables that measure business conditions show mixed results. As unemployment rises, bidding becomes more aggressive resulting in lower winning bids. This may reflect the fact that the firms non-highway business has weakened and they become more aggressive in bidding on procurement contracts. Alternatively, we expected to see less aggressive bidding as the volume of projects being let increased. This is not the case. Firms appear to bid somewhat more aggressively as the volume of projects increases although, again, there is no effect on the winning bids. The effect of a rise in building permits is not statistically significantly in most of the specifications.

PROJECT DIFFERENCES

The main results in Table 3 show a significant change in the average bidding behavior after the ECE policy change but no effect on winning bids. While the results in Table 3 offer an overall assessment of the impact of the change in ECE policy on bidding behavior in Oklahoma procurement auctions, the sample pools across projects with very different construction components. The theoretical literature in auctions suggests that the ECE information effect should be more pronounced in auctions where there is greater uncertainty about the cost. To examine the potential differences in the effect of ECE policy across projects, we look at two specific project types, asphalt and bridge work, where we think the relative importance of the common value components differ and where we have significant numbers of projects. Based on discussions with state highway and civil engineers, we believe that asphalt projects appear best described by the independent private value framework. Differences in bids submitted are primarily due to differences in private costs and there is less uncertainty in the costs involved. This is because asphalt projects are generally straightforward, requiring a contractor to lay down a certain thickness and type of asphalt across a specific road surface. For these projects, the quantities and types of material defined in the work items are usually well specified.

On the other hand, the costs associated with bridge construction and repair are often more uncertain. Each bridge is different and bridge construction projects will differ in complexity. Moreover, bridge work may require demolition and excavation in order to fully understand the costs of the job. The state construction engineers and civil engineers we spoke with generally thought that some costs associated with bridge work such as demolition and pier construction were more uncertain than the cost components typically observed in asphalt projects. The uncertainties may be due to the difficulties in assessing soil conditions or discerning the exact repairs that must be done to an existing bridge.[15] Table 4 shows some descriptive statistics for the asphalt and bridge work samples. Looking at the table, several patterns emerge. While all bids fall over time, there is a strong decline in the average relative bids in the bridge work category, especially in Oklahoma. The standard deviation of relative bids is also much higher in bridge work as compared to asphalt projects in both Texas and Oklahoma. Finally, the standard deviation in bridge work declines more sharply across time in Oklahoma compared with Texas. These patterns are certainly consistent with our story that bridge work projects contain more uncertain cost components and that the uncertainty is declining in Oklahoma.[16]

Our test will be to estimate a differences-in-differences model on asphalt and bridge projects separately using the same specification as presented in Table 3.[17] We expect to see a larger effect of the change in the ECE policy in the bridge project sample as compared to the asphalt sample. Table 5 presents the results for both asphalt and bridge models focusing on the relative bids variable. The asphalt results, in the first two columns, show there is no effect of the change in ECE policy on bids or winning bids for these projects in the post March 2000 period. There is a substantial rise in bids in the transition period for asphalt projects. For bridge projects, however, the coefficients that measure the change in bidding after the change in ECE policy are negative and large in magnitude. The results in column (3) show the average relative bid fell by about 9.6% for bridge projects. The winning relative bid also fell by a similar amount though it is statistically significant at only the 10% level. This differential impact of the information release across these project groups lends some confidence to the interpretation that the estimated differences-in-differences policy dummies are reflecting changes in the

[15] These uncertainties are reflected in the detailed work items listed in the project description. In bridge work, there are often unique construction tasks listed as "lump sum" items in the construction plans. For example, bridge demolition is usually listed as a "lump sum" cost item with no detailed breakdown of the specific costs of demolition. Alternatively, in asphalt projects an estimate of the amount of asphalt (e.g., in tons) to be used in a project will be clearly stated.

[16] Likewise, in an effort to categorize uncertainty in wildcat auctions, Porter (1995) concentrated on the large dispersion of submitted bids. Based on the variance in bids, he concluded that these auctions could be "regarded as common value auctions, where firms are uncertain about deposit sizes, common extraction costs, or future prices."

[17] This is similar to running a differences-in-differences-in-differences model where the project type dummy variable is fully interacted with all the variables in the model.

information environment. If the ECE policy variables were simply proxying for some other Oklahoma state level effect (e.g., budget issues), we would expect a uniform effect across these project types. This is not the case.

WITHIN-AUCTION VARIATION IN BIDS

The theory also predicts that when the common cost component is important, bids become more aggressive and more concentrated when information is released. This suggests the within-auction variation in bids should fall in response to ECE policy changes in auctions with a greater share of common cost components. In order to examine this issue, we estimate an econometric specification where the dependent variable is the within auction standard deviation of bids (*sdbid*). The specification is

$$sdbid_{at} = \alpha + \beta_1 D_t^{OK} + \beta_2 D_t^{TR} + \beta_3 D_t^{OK,TR} + \beta_4 D_t^{AF} + \beta_5 D_t^{OK,AF} + Z\Pi + \varepsilon_{at}. \qquad (4)$$

The standard deviation of bids is modeled as a function of the ECE policy dummies and a set of auction and business characteristics. We estimate the model across all auctions and for the asphalt and bridge work auctions separately. The data only contain auctions with four or more bidders because we need to construct an auction-specific standard deviation. We also use the range of bids (maximum bid – minimum bid) in an auction as an alternative measure of the dependent variable. Table 6 presents these results. There are two main findings. First, the results across all auctions show a substantial decline in both the standard deviation and the range of bids in Oklahoma after the ECE policy change (Column 1 and Column 4). Second, when comparing asphalt to bridge work auctions, the declines in the standard deviation and the range are larger in magnitude for the bridge projects. This is as expected if the release of information is reducing the uncertainty in common costs and common costs uncertainty is more prevalent in bridge projects.

QUANTILE REGRESSION ANALYSIS

In our analysis of bids, we have considered up to this point differences in the expected value, the variance and the range of values. We will now show that the level of bids is consistently lower in Oklahoma than in Texas not only in expectation but across the bidding distributions. We can thus provide additional evidence, beyond the graphs and the preceding statistical analysis, that the aggressive bidding behavior after the policy change is not due to a truncation of the distribution of bids at the upper end (for high cost bidders) but due to an informational effect that persistently affects bidding behavior at every level. This fact can be formalized in the analysis of the quantile regression model (see Koenker and Bassett, 1982) that follows.

This model allows us to estimate differences in the distribution of bids across bidders in Oklahoma and Texas before and after the policy change more accurately while taking into account other factors that contribute to the variability of bids. The advantage of employing quantile regression analysis at this point is that it allows a detailed examination of the difference between the distributions of bids not only at their mean level that could somewhat be driven by outliers but at the median, the 25th and 75th percentiles. The results of these estimations are presented in Table 7. The dependent variable in all regressions is the relative bid. The analysis employs similar specifications to those reported in column 1 of Table 3 and columns 1 and 3 of Table 5 (without a full set of the fixed effects).[18] The estimated coefficient of β_5 on the difference between the overall bids in Oklahoma and Texas after the policy change is the same in the .25 and .75 quantiles. The difference across the three quantiles tested from the models in columns 1 through 3 of Table 7 is statistically insignificant ($F(2, 13216) = .350$). The bids in Oklahoma are lower than those in Texas by 4.6% at the .50 quantile, holding everything else constant. That difference is almost the same as the expected difference reported in Table 3 but it represents the effect at the median level of bids which is less affected by outliers. Notice from columns 4 through 6 of Table 7 that the difference in the estimate of β_5 is statistically insignificant for asphalt work across the three quartiles and shows uniformly no difference in the bidding level across the two states after the policy change. When considering bridge work, there is no statistically significant difference in the estimate of β_5 across the quantiles, but all coefficients are statistically significant within each model signifying a large and persistent difference in the bidding behavior across the two states after the policy was implemented. For bridge projects, the median bid in Oklahoma after the policy change is 13.6% lower than in Texas.

[18] The model contains a set of individual firm dummies for the largest 35 firms in the sample. The remaining firms are modeled as a common intercept. We restricted the firm dummies to a manageable set for computation reasons.

ROBUSTNESS ANALYSIS

In the remaining part of the section, we estimate a number of alternative specifications in order to examine the robustness of our results. First, we consider the possibility that the standard errors in our model may be underestimated. While we have employed clustered standard errors throughout the paper to address the problems of within group correlation raised by Moulton (1990). Bertrand, Duflo, and Mullainathan (2004) raise the point that clustered standard errors are biased downward in panel data if serial correlation is present. One approach that Bertrand, Duflo and Mullainathan recommend is to collapse the time dimension of the data down to two periods – pre and post policy change. In our application, we aggregate the pre and post ECE policy data by firm and project type. Aggregation by firm within project types will allow for differences in response to the ECE policy change across project types seen in Table 5, while still collapsing the time dimension down into two periods. We require each firm to be bidding in both periods in order to estimate the fixed effects models and we drop the transition period data. Column 1 of Table 8 presents these results. The results are consistent with the model reported in Table 3 in terms of sign and statistically significance though the magnitude of the effect is substantially larger here. This increase in magnitude is most likely due to the fact that by aggregating across auctions our other control variables are less effective at controlling for differences in bidding across firms.

A second issue is whether the ECE policy variable is just picking up a declining trend in Oklahoma relative bids over time. To examine this matter, we estimate the relative bid model using only data from the pre-ECE policy change period and include trend variables to measure the trends in relative bids in Oklahoma and Texas over this period. The model includes an overall trend term and the trend term interacted with a dummy variable for Oklahoma auctions to test for cross-state differences in trend. The second column of Table 8 contains these results. The estimated trend terms are not individually statistically significant and show no statistical difference between Oklahoma and Texas. Hence, Oklahoma's relative bids were not trending downward prior to the ECE policy change either in an absolute sense or relative to Texas.

We also estimated our models altering our clustering approach. Throughout the paper, we have chosen to cluster by firm. An alternative approach is to cluster by auction. This raises the number of clustering groups significantly (3608 clusters) and subsequently decreases the number of observations per group. The third column of Table 8 provides these results. The ECE remains statistically significant and the standard errors are almost identical under both clustering approaches.

A third test that we perform deals with a special group of auctions in Oklahoma that we refer to as repeated auctions. Repeated auctions are auctions of projects that failed to be auctioned off in an initial attempt. For these projects, bidders have a very good idea of the engineering estimate in *all periods* because in the initial round the engineering estimate is released and, thus, the effect of the change in ECE information policy in this sub-sample should be small. We perform our empirical test by adding the repeated Oklahoma auction data to our Oklahoma-Texas sample and estimate the panel-data differences-in-differences model with a set of dummy variables that control for bidding in repeated auctions. If the repeated auctions have the same pattern in coefficients as the non-repeated auctions in Oklahoma, then this would suggest that the time period effects may be picking up some other shocks that are specific to Oklahoma but not related to the ECE information policy change. The fourth column of Table 8 reports the results of models that include the repeated auctions in our empirical analysis. The repeated auction coefficients indicate no decline in bids in the repeated auction after the change in ECE policy. A joint statistical test of the three coefficients cannot reject the hypothesis that bidding in the repeated auctions is no different than in Texas auctions ($F(3, 491) = .300$). However, one should be cautious here in over-interpreting the repeated auction test as a comparison to a randomly selected control group. This is clearly not the case. The repeated auctions represent projects that failed to be awarded in an initial auction primarily because the submitted bids were too high or because no firms bid on the project. This lower level of competition in these auctions is reflected in the bidding statistics presented in Table 2c.

A last exercise we perform considers the possibility that the actual number of bidders may not be the best measure of potential competition in these settings (Hendricks, Pinske and Porter (2003)). In our case, the actual number of bidders is not known to participants. To see the sensitivity of our results to the assumption that the number of bidders is given, we re-estimate the model replacing the number of bidders with a variable that measures the expected number of bidders. The expected number of bidders is constructed using information on past bidding history of all plan holders in an auction. The number of plan holders and the identity of the plan holders are known to all bidders before bids are submitted. For each plan holder at time *t*, we sum up their past number of bids and divide this by their past number of plans held. This gives a probability of bidding for each plan holder. Then for an auction at time *t*, we sum across these participation probabilities for all plan holders in an auction and this yields our measure of the expected number of bidders. Since the identity of the plan holders is known to all potential bidders, an estimate of the expected number of bidders can be constructed by bidders in such a way prior to the bid submission. Column 5 of Table 8 presents the results. The coefficient on the expected number of bidders is somewhat smaller in magnitude than that reported in Table 3 though it remains negative and statistically significant. More importantly, our results on the ECE policy variable remain unchanged to this modification in the specification. Finally, estimated models (not shown) on the asphalt and bridge work project samples using expected number of bidders instead of the number of bidders are also consistent with findings reported in Table 5.

V. INFORMATION POLICY EFFECTS ON THE NUMBER OF BIDDERS

While the above analysis has examined the direct effect of change in ECE policy on bids, another channel by which the policy change could affect bidding is through the number of bidders. When the state reveals the ECE, it provides additional information about the cost and the likely reserve price of the project. If bidders base their decision to submit a bid on this type of information, then the number of bidders is likely to be affected by the ECE, as well.

Our current model, assumes that $dE[rbid \mid x]/dokafter = \partial E[rbid \mid x]/\partial okafter$ and measures the effect of the change in the ECE policy by the estimate of β_5. However, if the ECE policy variable also affects the number of bidders, then our expression for the policy effect on bids should be $dE[rbid \mid x]/dokafter = \beta_5 + \beta_n \cdot \partial N/\partial okafter$, where β_n is the coefficient on the number of bidders in the relative bids model. In order to estimate the effect of the ECE policy change on number of bidders ($\partial N/\partial okafter$), we estimate a count-data model (Poisson) of the number of bidders on the ECE policy variables along with a set of control variables. These control variables include project size, detailed project location dummies, project type dummies, monthly dummies, and business condition variables. We also estimate a similar model using the number of plan holders (i.e., the number of potential bidders). Columns (1) and (2) of Table 9 report the results from these count data models for the number of plan holders and number bidders, respectively.[19] The unit of observation here is an auction. Focusing on the post-ECE policy change parameter, we see that the post-ECE policy parameter is not statistically significant in the number of plan holders' equation. There is, however, a statistically significant effect on the number of bidders. The number of bidders decreases in Oklahoma relative to Texas in the post-ECE policy change period. The magnitude of the effect, calculated as the average response, is a decline of .440 bidders in Oklahoma.[20] It should be noted that this is the relative average response in Oklahoma compared to Texas. In fact, in both Texas and Oklahoma the absolute number of bidders rises in the post-ECE policy change period compared to the pre-ECE policy change period. Plugging the estimates from the relative bid model in Table 3 and the average response calculated from the Poisson model into the expression $dE[rbid \mid x]/dokafter$ = $\beta_5 + \beta_n \cdot \partial N / \partial okafter$, yields an effect of -.043={-.050-.015×(-.440)}. We test the statistical significance of the overall effect using a Wald test. The Chi-square statistic from this test is 4.42 with a p-value of .036.[21] Hence, our overall estimate of the effect of the ECE policy change on relative bids remains statistically significant at the 5% level.

While the main concern of the paper is not on the number bidders, if the number of bidders is endogenous it may affect our estimates of the ECE policy parameters, the estimate of β_n from the original equation, and therefore the estimate of the overall effect the ECE policy change. In an effort to address this issue, we re-estimate the model using

[19] An assumption of the poisson model is that mean and variance of the distribution of counts is the same. In our application, the mean and variance of numbids are almost identical being 3.70 and 3.78, respectively. In a test of overdispersion, we cannot reject the null hypothesis of no overdispersion. This is not true in the case of the number of plan holders where overdisperson is a problem. However, we do not use the estimates from the poisson model on the number of plan holders in our calculation of the overall effect.

[20] The average response for the effect of post ECE policy change on the number of bidders is calculated as the $\alpha_{okafter}$ x N^{-1} Σ_a $\exp(x_i^{'}\alpha)$ where the α's are the parameters estimated in the poisson model.

[21] We estimate the relative bids and Poisson using a seemingly unrelated regression approach that allows for clustered standard errors and between model covariance in the estimated parameter estimates. Given that the Poisson model is at the auction level, the models are estimated with clustering at the auction level. Clustering using auctions actually increases the standard errors in the relative bid model slightly more than when using firm clusters. This is reported above in Table 8.

instrumental variable techniques where our instrument for the number of bidders is the number of plan holders. There are two requirements for a valid instrument in this application. It must be correlated with the number of bidders and uncorrelated with the error term in the relative bids equation. The number of plan holders is certainly strongly correlated with the number of bidders in an auction since it identifies the maximum number of bidders that appear in an auction. With respect to the correlation between the number plan holders and the error term, we argue the number of plan holders will be relatively uncorrelated with the error term in the bidding equation.

As we mentioned above, the number of plan holders and the identity of plan holders is known to all bidders prior to bid submission. So, the number of plan holders is clearly not affected by the bids submitted. Now consider an error structure that would cause us problems. Let the error term in equation (3) be $\varepsilon_{iat} = \mu_i + \mu_a + \mu_{iat}$, where μ_i is a firm specific error component, μ_a is an auction specific error component and μ_{iat} is a white noise component. The firm effects already included in the model control for the firm specific component. The model cannot include auction specific effects because our interest is in estimating the effects of the ECE policy variables on bidding and there is no within auction variation is the ECE policy variables. The endogeneity in the number of bidders arises if the Cov(Number of Bidders, μ_a) $\neq 0$. This says there is some auction specific factor that is uncontrolled for in the regression and is correlated with the number of bids. For example, this could be due to some specialized input required to complete a project that affects both the level of bids and number of bidders. However, μ_a is likely to be observed by a potential bidder only after the firm purchases a plan and, hence, there should be little correlation between μ_a and the decision to purchase a plan. Moreover, plans are very inexpensive costing around \$25 for a project, so there would be little incentive for a firm to formulate an independent estimate of μ_a without purchasing a plan. Now it is true that when bidders see a high (low) number of plan holders they may bid more (less) aggressively but they do so *only* because the number of bidders is likely to be higher (lower) when there are more (less) plan holders in an auction. We can think of no other reason why the number of plan holders should affect the bids submitted except through its influence on the number of bidders. Therefore, we do not believe there is an independent plan holder effect on bids.

The IV model is estimated using two-stage least squares with clustered standard errors. The third and fourths column of Table 9 show the results of this exercise. Column 4 presents the IV results while column 3 shows the results from the basic OLS model discussed earlier for comparison purposes. As one can see, there is little difference between the OLS and IV results. The Hausman test reported at the bottom of the table indicates we cannot reject the null hypothesis that the OLS and IV models yield similar estimates. The results also show, as expected, that the number of plan holders is highly correlated with the number of bidders in the first stage regression. There are two main conclusions we draw from this IV exploration. First, it is reasonable to use our estimate of β_n from the OLS in calculating the overall effect of the ECE policy change on relative bids. Second, the sign and magnitude of the parameters on the ECE policy variables are insensitive to the choice of IV or OLS estimation techniques.

VI. CONCLUSION

This paper contributes to the empirical literature on auctions by providing an examination of the impact of the release of information on bidding behavior in procurement auctions. Our analysis of the bidding data produced three main empirical findings. First, in comparison to Texas auctions, the average bid in Oklahoma declines after the change in ECE policy. Second, bids drop sharply in bridge work but not in asphalt projects. Third, the variation in bids falls after the change in ECE policy and the magnitude of this decline is larger for bridge projects compared to asphalt projects. These three results are in agreement with the predictions of the theory. The release of seller information generally leads to lower bids. In Oklahoma, these lower average bids do not result in lower winning bids across all projects and hence do not result in lower procurement costs, on average. This raises the concern that the release of information may be affecting only the upper end of bid distribution. However, the quantile regression results along with the basic patterns observed in Figure 1 show that the effect of the ECE policy variable is relatively uniform across the quantiles. Moreover, in bridge work where we expected to see a larger impact, we do observe a decline in winning bids that is similar in magnitude to the decline in the average bid. Even after we account for implicit effects through a potential change in the number of bidders submitting bids, the effect of the ECE policy change on relative bids remains strong and statistically significant. Alternatively, we find no evidence that the change in information policy led to an increase in relative bids in two and half years since the policy changed. This is an important outcome to rule out as federal and state transportation officials have raised concerns that the releasing of the ECE estimate prior to bid letting may lessen competition.

APPENDIX A

Derivation of the bidding function:

Consider a bidder's expected payoff from participation:

$$\pi(b) = [b - s - \frac{n-1}{n} E[v \mid s \geq B^{-1}(b)]][1 - F_s(B^{-1}(b))]^{n-1}.$$

Differentiating the expected payoff with respect to b and evaluating the expression at the optimal choice we have:

$$\left.\frac{\partial \pi}{\partial b}\right|_{b=B(x)} = \left[1 - \frac{n-1}{n}(E[v \mid s \geq x] - E[v \mid s = x])\frac{1}{B^{'}(x)}\frac{f_s(x)}{1 - F_s(x)}\right][1 - F_s(x)]^{n-1}$$

$$-\left[B(x) - s - \frac{n-1}{n} E[v \mid s \geq x]\right](n-1)[1 - F_s(x)]^{n-2} f_s(x)\frac{1}{B'(x)} = 0$$

Simplifying we get:

$$[\frac{1}{n-1} - \frac{1}{n}(E[v \mid s \geq x] - E[v \mid s = x])\frac{1}{B^{'}(x)}\frac{f_s(x)}{1 - F_s(x)}][1 - F_s(x)] -$$

$$[B(x) - s - \frac{n-1}{n} E[v \mid s \geq x]]\frac{f_s(x)}{B^{'}(x)} = 0 \qquad \Leftrightarrow$$

$$[\frac{1 - F_s(x)}{f_s(x)}\frac{B^{'}(x)}{n-1} - \frac{1}{n}(E[v \mid s \geq x] - E[v \mid s = x]) - B(x)$$

$$+ s + \frac{n-1}{n} E[v \mid s \geq x]]\frac{f_s(x)}{B^{'}(x)} = 0 \qquad \Leftrightarrow$$

$$[\frac{1-F_{y_1}(x)}{f_{y_1}(x)}B^{'}(x)+\frac{1}{n}(E[v\mid s=x]+\frac{n-2}{n}E[v\mid s\geq x])-B(x)$$
$$+s]\frac{f_s(x)}{B^{'}(x)}=0. \tag{A1}$$

We can now show that the following function is indeed the symmetric equilibrium bidding strategy for bidder *i* in the first price auction:

$$B(x)=\frac{n-1}{n}E[v\mid s\geq x]+E[y_1\mid y_1\geq x]. \tag{A2}$$

Using the fact that

$$E[v\mid X\geq x]=\int_{x}^{x_H}E[v\mid x=w]\frac{f_x(w)}{(1-F_x(x))}dw$$

and differentiating (A2) we get:

$$B'(x)=\frac{n-1}{n}(E[v\mid s\geq x]-E[v\mid s=x])\frac{f_s(x)}{1-F_s(x)}$$
$$+[E[y_1\mid y_1\geq x]\text{ - x}]\frac{f_{y_1}(x)}{1-F_{y_1}(x)} \tag{A3}$$

Replacing (A2) & (A3) into (A1) we get:

$$\frac{1}{n}(E(v\mid s\geq x)-E(v\mid s=x))+(E(y_1\mid y_1\geq x)-x)$$
$$+\frac{1}{n}E(v\mid s=x)+\frac{n-2}{n}E(v\mid s\geq x)$$
$$-\frac{n-1}{n}E(v\mid s\geq x)-E(y_1\mid y_1\geq x)+s]\frac{f_s(x)}{B'(x)}=0$$
$$[s-x]\frac{f_s(x)}{B'(x)}=0\Rightarrow s=x.$$

Together with the monotonicity of *B*, this shows that $B(s_i)$ is the bidder's unique optimal bid, i.e.,

$$B(s_i)=\frac{n-1}{n}E[v\mid s\geq s_i]+E[y_1\mid y_1\geq s_i].$$

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Figure 1: Kernel Density Plot of Relative Bids on all Project Types for Oklahoma before November 1999, from Nov 1999 to March 2000, and after March 2000

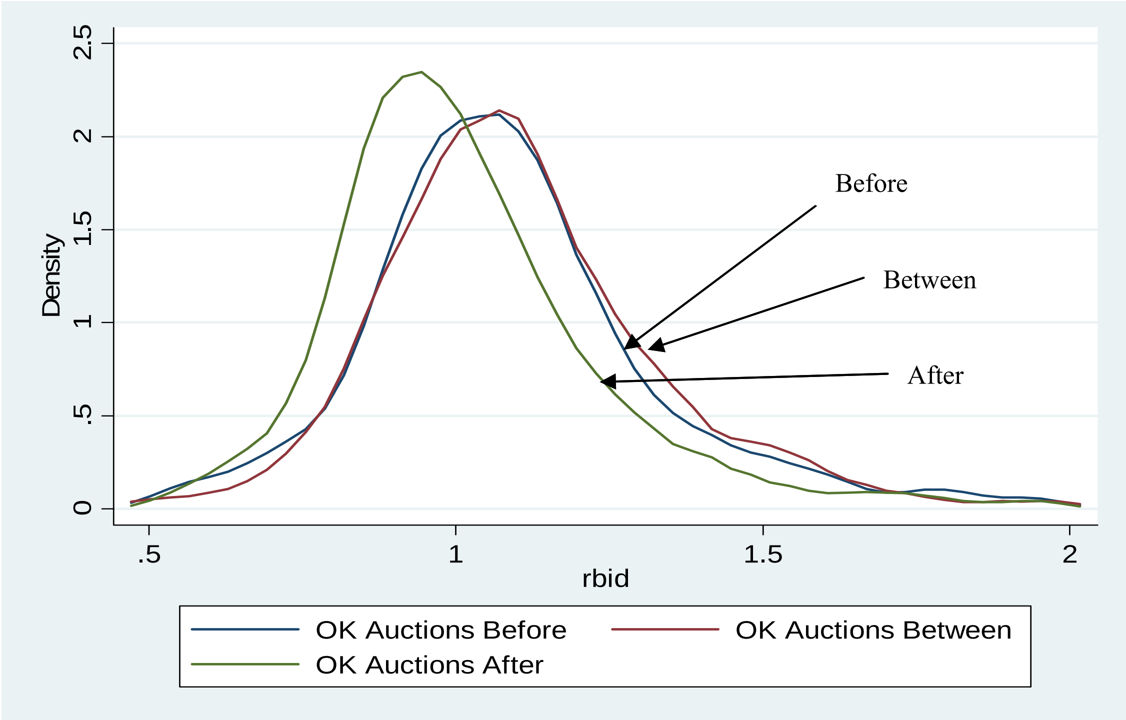

Figure 2: Kernel Density Plot of Relative Bids on all Project Types for Texas Districts that Border Oklahoma before November 1999, from Nov 1999 to March 2000, and after March 2000

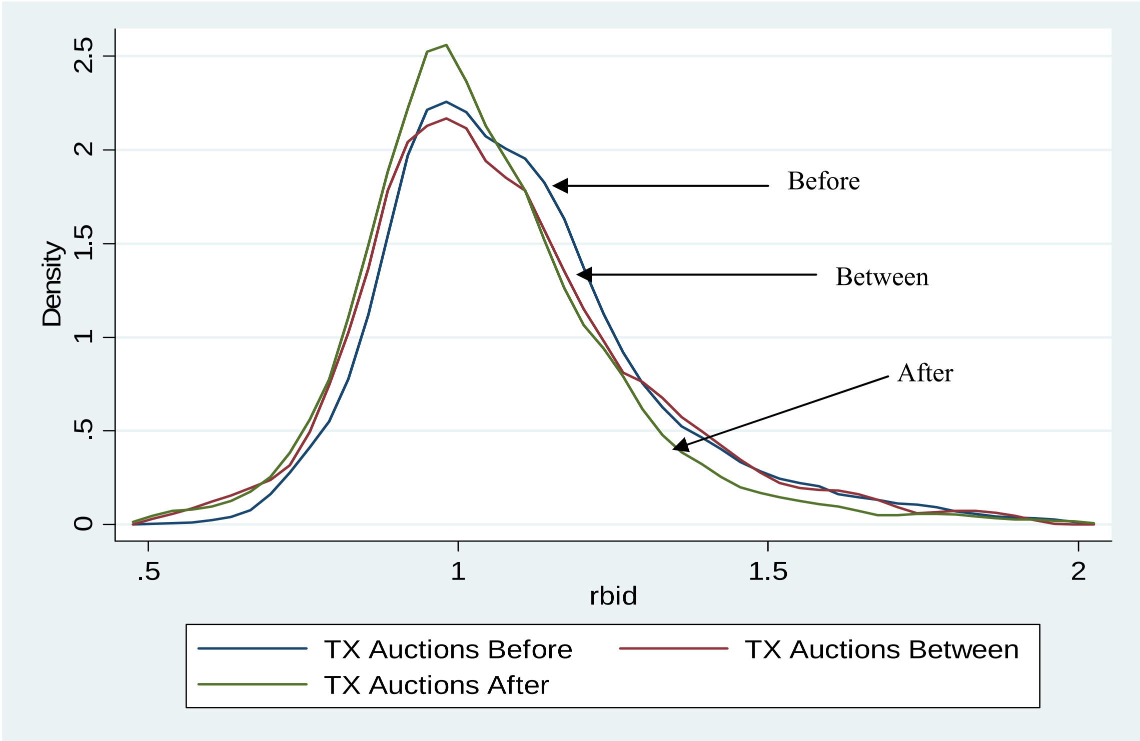

Figure 3: Ratio of Quarterly Real Volume to Average Real Volume of Projects in Oklahoma and Texas

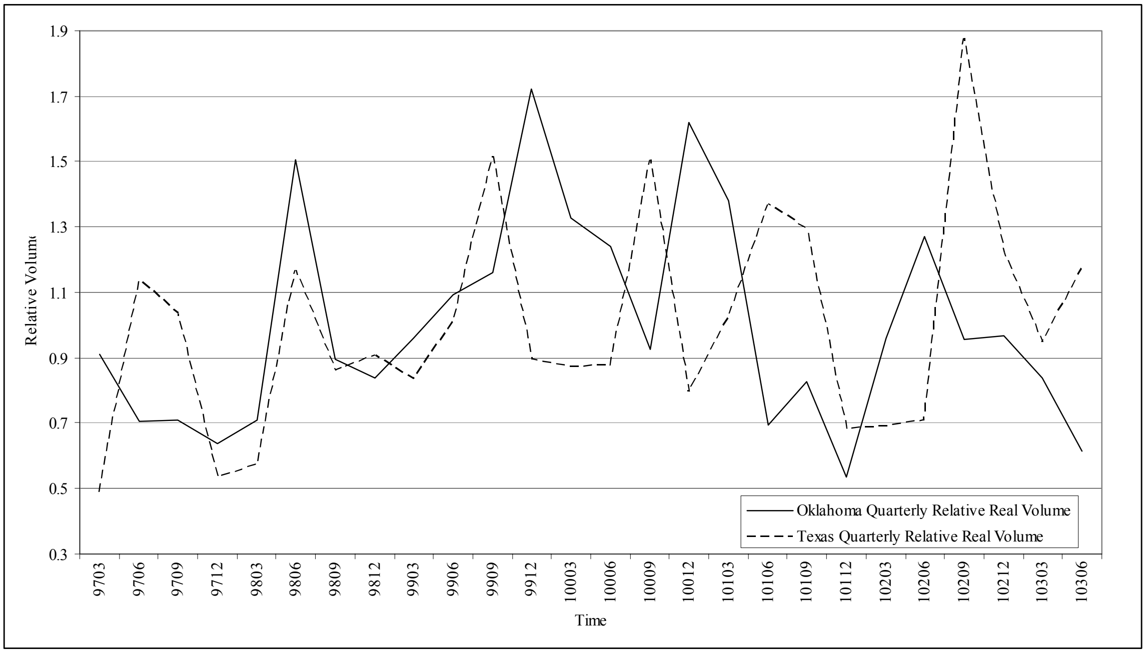

Figure 4: Unemployment Rates for Oklahoma and Texas

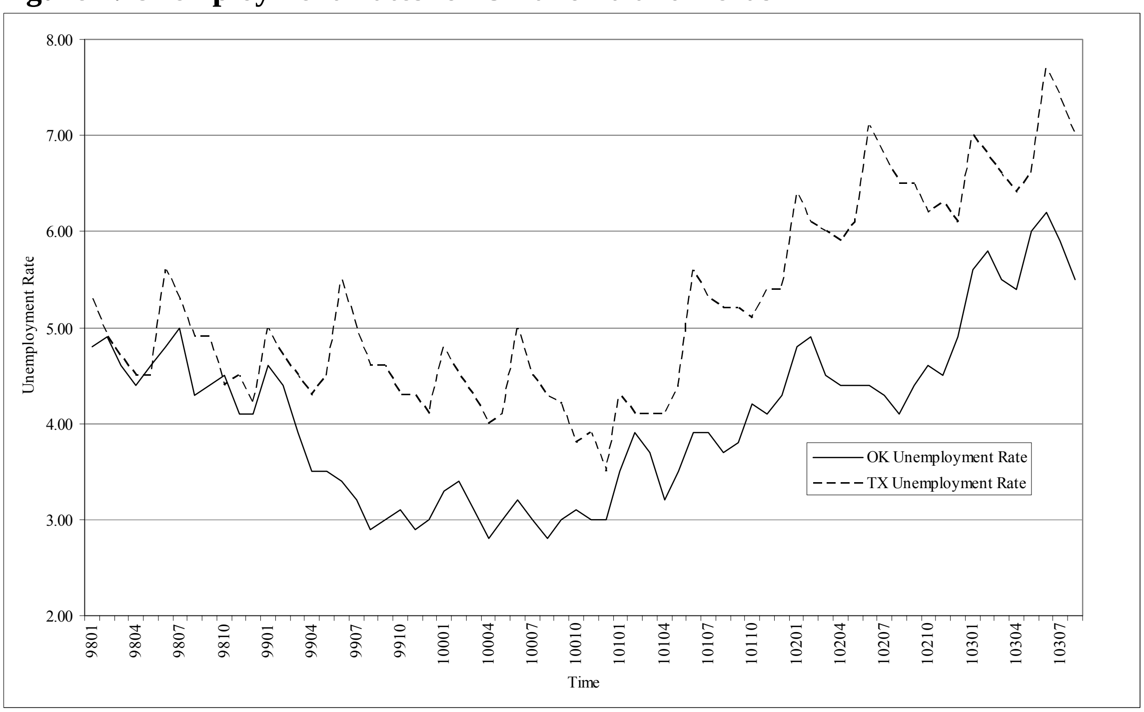

Table 1: State Policies on ECE information release

ECE Policy	State
No release before the bid letting - ECE release after	AK, AZ, CO, DE, GA, ID, IN, KY, ME, MN, NM, OH, SC, TN, WV
No release before or after the bid letting	AR, IL, IA, KS, MD, NE, VT, VA
Release of a range of values before- no release after	AL, NJ, MO, WI
Release of a range of values before- ECE release after	CT, HI, MS, MT, NY, ND, OR, WA, WY, PA
Release of a budgeted estimate before- ECE release after	CA, FL, SD, NC
Release of a budgeted estimate before- no ECE release after	RI
ECE release before	LA, MA, MI, NV, OK, TX, UT, NH

Table 2a: Summary Statistics for Oklahoma Auctions

Variable	Before November 1999	From November 1999 to March 2000	After March 2000
Total number of auctions	698	143	1220
Number of awarded projects	620	116	1072
Average number of plan holders	5.536	6.308	6.257
	(3.010)	(3.499)	(3.590)
Average number of bidders	3.132	3.300	3.475
	(1.565)	(1.754)	(1.786)
Relative value of bids	1.117	1.112	1.027
	(.363)	(.277)	(.295)
Relative value of winning bids	.968	.961	.906
	(.200)	(.171)	(.197)

Standard deviations are in parentheses**.**

Table 2b: Summary Statistics for Texas Districts that Border Oklahoma Auctions

Variable	Before November 1999	From November 1999 to March 2000	After March 2000
Total number of auctions	527	108	913
Number of awarded projects	506	104	891
Average number of plan holders	6.167	6.824	7.404
	(3.907)	(3.289)	(3.486)
Average number of bidders	3.613	4.157	4.588
	(1.654)	(1.958)	(2.207)
Relative value of bids	1.105	1.071	1.051
	(.240)	(.229)	(.248)
Relative value of winning bids	1.011	.986	.942
	(.179)	(.205)	(.183)

Standard deviations are in parentheses.

Table 2c: Summary Statistics for Oklahoma Repeated Auctions

Variable	Before November 1999	From November 1999 to March 2000	After March 2000
Total number of auctions	53	27	60
Number of awarded projects	27	20	41
Average number of plan holders	4.943	5.407	5.383
	(2.274)	(2.576)	(2.630)
Average number of bidders	2.830	3.259	2.683
	(1.236)	(1.933)	(1.049)
Relative value of bids	1.195	1.138	1.168
	(.324)	(.175)	(.382)
Relative value of winning bids	.934	1.011	1.028
	(.094)	(.072)	(.248)

Standard deviations are in parentheses**.**

Table 3: Panel Fixed-Effects Differences-in-Differences Estimates

Variable	Base Model			
	Relative Bids (1)	**Relative Winning Bids (2)**	**Log of Bids (3)**	**Log of Winning bids (4)**
Oklahoma bids (β_1)	.002	-.042	-.059	-.037
	(.066)	(.037)	(.062)	(.024)
Bids from November 1999 to March 2000 (β_2)	-.034**	-.018	-.019*	-.017
	(.013)	(.022)	(.010)	(.022)
Oklahoma bids from November 1999 to March 2000 (β_3)	.038	.015	.044**	.026
	(.024)	(.028)	(021)	(.030)
Bids after March 2000 (β_4)	-.034**	-.031**	-.016*	-.027*
	(.010)	(.014)	(.009)	(.015)
Oklahoma bids after March 2000 (β_5)	-.050**	-.014	-.040**	-.016
	(.020)	(.015)	(.016)	(.016)
Number of bidders	-.015**	-.025**		
	(.002)	(.003)		
Log number of bidders			-.066**	-.134**
			(.010)	(.015)
Log of engineer's estimate			.957**	.982**
			(.004)	(.005)
Capacity utilized	.012	.027*	.018*	.028*
	(.011)	(.015)	(.010)	(.017)
Distance to the project location	.006	.003	.008**	.004
	(.004)	(.002)	(.003)	(.003)
Average rivals winning to plan holder ratio	-.058	-.201**	-.165**	-.212**
	(.081)	(.066)	(.064)	(.073)
Closest rival's distance to the project location	.001	.003	.000	.004
	(.002)	(.002)	(.002)	(.003)
Rivals minimum backlog	-.000	.000	.000	-.000
	(.001)	(.001)	(.000)	(.001)
Seasonally unadjusted unemployment rate	-.012**	-.009*	-.012**	-.012*
	(.005)	(.005)	(.004)	(.006)
Three month average of the real volume of projects	-.023*	-.015	-.020*	-.020
	(.012)	(.014)	(.011)	(.016)
Three month average of the number of building permits	.034	.019	.046*	.025
	(.036)	(.040)	(.028)	(.046)
Number of Observations	13282	3222	13282	3222
Adj-R^2	.136	.213	.983	.988

**Denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. Robust clustered standard errors using firm level-clusters are in parentheses. All regressions include firm-level fixed effects, five project class dummy variables, and 11 monthly dummy variables.

Table 4: Summary Statistics for Asphalt and Bridge Work Projects

Variable	Full Sample		For Oklahoma		For Texas Districts that Border Oklahoma	
	Asphalt	**Bridge**	**Asphalt**	**Bridge**	**Asphalt**	**Bridge**
Mean of the Relative Bids Before Nov 1999	1.088	1.152	1.086	1.154	1.090	1.148
	(.214)	(.384)	(.211)	(.425)	(.217)	(.294)
Mean of the Relative Bids After March 2000	1.040	1.061	1.053	1.038	1.033	1.106
	(.199)	(.342)	(.196)	(.362)	(.201)	(.292)

Standard deviations are in parentheses.

Table 5: Panel Fixed-Effects Differences-in-Differences Estimates for Asphalt and Bridge Projects.

Variable	Asphalt Projects		Bridge Projects	
	Relative Bids (1)	Relative Winning Bids (2)	Relative Bids (3)	Relative Winning Bids (4)
Oklahoma bids (β_1)	.036	.036	.019	.299**
	(.058)	(.127)	(.153)	(.104)
Bids from November 1999 to March 2000 (β_2)	-.027	-.014	-.043	.005
	(.016)	(.026)	(.033)	(.073)
Oklahoma bids from November 1999 to March 2000 (β_3)	.150**	.093**	-.003	-.059
	(.041)	(.037)	(.055)	(.086)
Bids after March 2000 (β_4)	-.030**	-.003	-.029	.021
	(.012)	(.015)	(.030)	(.047)
Oklahoma bids after March 2000 (β_5)	.012	-.010	-.096**	-.090*
	(.019)	(.022)	(.039)	(.053)
Number of bidders	-.018**	-.030**	-.018**	-.022**
	(.002)	(.004)	(.004)	(.005)
Capacity utilized	.018	.001	-.012	.052
	(.012)	(.021)	(.024)	(.042)
Distance to the project location	.008**	.001	-.002	.009
	(.003)	(.003)	(.012)	(.009)
Average rivals winning to plan holder ratio	-.063	-.129*	-.011	-.226
	(.067)	(.074)	(.236)	(.174)
Closest rival's distance to the project location	-.005**	-.001	-.001	.005
	(.002)	(.003)	(.004)	(.005)
Rivals minimum backlog	-.001**	-.001	.000	-.000
	(.000)	(.001)	(.004)	(.002)
Seasonally unadjusted unemployment rate	-.006	.000	-.021*	-.017
	(.005)	(.008)	(.011)	(.012)
Three month average of the real volume of projects	-.009	-.008	-.058**	-.026
	(.014)	(.013)	(.026)	(.038)
Three month average of the number of building permits	.100**	.032	-.034	.039
	(.035)	(.061)	(.080)	(.078)
Number of Observations	3962	1052	4569	1011
Adj-R^2	.177	.289	.120	.181

**Denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. Robust clustered standard errors using firm-level clusters are in parentheses. All regressions include firm-level fixed effects and 11 monthly dummy variables.

Table 6: Estimates of Bid Dispersion Model

Variable	Standard Deviation			Range		
	All Projects (1)	**Asphalt Projects (2)**	**Bridge Projects (3)**	**All Projects (4)**	**Asphalt Projects (5)**	**Bridge Projects (6)**
Oklahoma bids (β_1)	.054**	.036**	.090**	.130**	.077**	.221**
	(.013)	(.014)	(.026)	(.032)	(.035)	(.066)
Bids from November 1999 to March 2000 (β_2)	.017	.008	-.004	.040	.007	-.004
	(.015)	(.014)	(.027)	(.040)	(.031)	(.069)
Oklahoma bids from November 1999 to March 2000 (β_3)	-.044	.047	-.015	-.125*	.102	-.065
	(.029)	(.054)	(.063)	(.071)	(.131)	(.143)
Bids after March 2000 (β_4)	.014*	.002	.013	.031*	.003	-.029
	(.007)	(.008)	(.019)	(.018)	(.019)	(.048)
Oklahoma bids after March 2000 (β_5)	-.044**	-.030*	-.061*	-.107**	-.064	-.151**
	(.015)	(.016)	(.031)	(.037)	(.040)	(.075)
Number of bidders	-.004**	-.005**	-.012**	.010**	.002	-.003
	(.002)	(.002)	(.004)	(.004)	(.004)	(.010)
Seasonally unadjusted unemployment rate	.001	.001	.004	.003	.001	.014
	(.004)	(.005)	(.010)	(.011)	(.012)	(.024)
Three month average of the real volume of projects	.028**	.005	.028	.067**	.015	.066
	(.010)	(.019)	(.020)	(.025)	(.045)	(.047)
Three month average of the number of building permits	.013	.013	-.096	.047	.036	-.224
	(.037)	(.040)	(.074)	(.093)	(.096)	(.189)
Number of Observations	1651	460	629	1651	460	629
Adj-R^2	.111	.052	.080	.123	.026	.070

**Denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. Robust standard errors are in parentheses. All regressions include a constant term and 11 monthly dummy variables. Regression in columns 1 and 4 includes five project type dummy variables.

Table 7: Quantile Regression Estimates for Relative Bids

Variable	Base Model			Asphalt Projects			Bridge Projects		
	.25	**.50**	**.75**	**.25**	**.50**	**.75**	**.25**	**.50**	**.75**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Oklahoma bids (β_1)	-.032**	-.019*	-.018	-.002	-.013	-.035	-.038*	.004	.019
	(.010)	(.011)	(.014)	(.016)	(.017)	(.022)	(.021)	(.020)	(.031)
Bids from November 1999 to March 2000 (β_2)	-.027**	-.006	.019	-.022	-.015	-.005	-.029	.003	.008
	(.010)	(.016)	(.025)	(.017)	(.021)	(.021)	(.022)	(.023)	(.051)
Oklahoma bids from November 1999 to March 2000 (β_3)	.048**	.029	.012	.113**	.111**	.169**	.032	-.017	-.010
	(.018)	(.020)	(.029)	(.023)	(.036)	(.055)	(.039)	(.037)	(.073)
Bids after March 2000 (β_4)	-.026**	-.025**	-.034**	-.016	-.041**	-.027*	.002	.022	-.012
	(.006)	(.008)	(.011)	(.011)	(.012)	(.014)	(.011)	(.014)	(.021)
Oklahoma bids after March 2000 (β_5)	-.038**	-.046**	-.044**	-.003	.028	.016	-.104**	-.136**	-.122**
	(.010)	(.011)	(.014)	(.015)	(.017)	(.024)	(.018)	(.019)	(.027)
Number of Observations	13282	13282	13282	3962	3962	3962	4569	4569	4569
Pseudo-R^2	.043	.041	.054	.042	.047	.057	.066	.057	.072

**Denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. The reported standard errors are bootstrap standard errors using 100 replications. All regressions include a constant term, 35 large firm dummies, and 11 monthly dummy variables. Regression in columns 1-3 includes five project type dummy variables.

Hypothesis test results for H_o: $\beta_5^{.25} = \beta_5^{.50} = \beta_5^{.75}$

1) Base model: F(2, 13216) = .350
2) Asphalt projects: F(2, 3910) = 1.690
3) Bridge projects: F(2, 4534) = 1.420

Table 8: Alternate Specifications and Robustness Checks

Variable	Pre-Relative Bids – Averaged by Period and Project Types (1)	Relative Bids			
		Time Trend Analysis (2)	Standard Errors Clustered by Auctions (3)	Repeated Auctions (4)	Expected Number of Bidders (5)
Oklahoma bids (β_1)	.006	-.100	.002	-.005	-.006
	(.091)	(.057)	(.038)	(.065)	(.063)
Bids from November 1999 to March 2000 (β_2)			-.034*	-.035**	-.037**
			(.020)	(.013)	(.013)
Oklahoma bids from November 1999 to March 2000 (β_3)			.038	.042*	.040*
			(.033)	(.023)	(.023)
Bids after March 2000 (β_4)	-.083**		-.034**	-.033**	-.040**
	(.027)		(.013)	(.010)	(.010)
Oklahoma bids after March 2000 (β_5)	-.109**		-.050**	-.048**	-.045**
	(.037)		(.021)	(.020)	(.010)
Time		.001			
		(.001)			
Time Oklahoma bids*		.000			
		(.001)			
Repeated auctions				-.020	
				(.064)	
Repeated auctions in Oklahoma from 1999:11 to 2000:3				.042	
				(.054)	
Repeated auctions in Oklahoma after 2000:3				.023	
				(.043)	
Expected Number of Bidders					-.010**
					(.001)
Number of Observations	942	4088	13282	13684	13282
Adj-R^2	.293	.181	.136	.142	.132

**Denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. All regressions include firm-level fixed effects and five project type dummy variables. Columns 3—6 include 11 monthly dummy variables. All regressions other than in column 3 report robust clustered standard errors using firm-level clusters. In column 3 robust clustered standard errors using auction level clusters are in parentheses.

Table 9: Number of Bidders Analysis

Variable	Poisson		Relative Bids	
	Number of Plan Holders	Number of Bidders	Base Model	Instrumented with Number of Plan Holders
	(1)	(2)	(3)	(4)
Oklahoma bids (β_1)			.002	.002
			(.066)	(.067)
Bids from November 1999 to March 2000 (β_2)	.069	.100**	-.034**	-.034**
	(.048)	(.048)	(.013)	(.013)
Oklahoma bids from November 1999 to March 2000 (β_3)	-.012	-.019	.038	.038
	(.064)	(.067)	(.024)	(.024)
Bids after March 2000 (β_4)	.161**	.202**	-.034**	-.033**
	(.027)	(.026)	(.010)	(.10)
Oklahoma bids after March 2000 (β_5)	-.049	-.119**	-.050**	-.050**
	(.354)	(.037)	(.020)	(-.020)
Log of Engineering Estimate	-.298**	-.210**		
	(.067)	(.063)		
Log of Engineering Estimate^2	.015**	.010**		
	(.002)	(.002)		
Number of bidders			-.015**	-.015**
			(.002)	(.002)
Capacity utilized			.012	.012
			(.011)	(.011)
Distance to the project location			.006	.006
			(.004)	(.004)
Average rivals winning to plan holder ratio			-.058	-.058
			(.081)	(.083)
Closest rival's distance to the project location			.001	.001
			(.002)	(.002)
Rivals minimum backlog			-.000	-.000
			(.001)	(.001)
Seasonally unadjusted unemployment rate	.061**	.060**	-.012**	-.012**
	(.012)	(.013)	(.005)	(.005)
Three month average of the real volume of projects	-.036	-.197*	-.023*	-.023**
	(.098)	(.103)	(.012)	(.009)
Three month average of the number of building permits	-.098**	-.119**	.034	.034
	(.028)	(.029)	(.036)	(.037)
First Stage Instrument				
Number of plan holders				.412**
				(.008)
Number of Observations	3634	3634	13282	13282
Adj-R^2			.136	.136
Wald χ^2	1841.17	996.22		
Hausman Test (P-value)				.93

**Denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. In columns 1 and 2 robust standard errors are in parentheses. In columns 3 and 4 robust clustered standard errors using firm-level clusters are in parentheses. The Poisson models in columns (1) and (2) include 14 project location dummies, five project type dummy variables, and 11 monthly dummy variables. The models in columns (3) and (4) include firm-level fixed effects, five project type dummy variables, and 11 monthly dummy variables.

APPENDIX B: SUPPLEMENTARY TABLES

Table B1: Regression Variables

Independent Variable	**Description and Construction of the Independent Variable**
Relative bid	Bid divided by the ECE.
Relative winning bid	Winning bid divided by the ECE.
Log of the Bid	The logarithm of the bid.
Log of the winning bid	The logarithm of the winning bid.
Auctions specific standard deviation of relative bids	The standard deviation of relative bids for a given auction.
Auctions specific range of relative bids	The auctions specific range is calculated as the maximum relative bid minus the lowest relative bid.
Oklahoma bids	A dummy variable that identifies the bids in the state of Oklahoma.
Bids from November 1999 to March 2000	A dummy variable that identifies the period between November 1999 and March 2000.
Oklahoma bids from November 1999 to March 2000	A dummy variable that identifies the bids in the state of Oklahoma between November 1999 and March 2000.
Bids after March 2000	A dummy variable that identifies the period after March 2000.
Oklahoma bids after March 2000	A dummy variable that identifies the bids in the state of Oklahoma after March 2000.
Repeated Auctions in Oklahoma	A dummy variable that identifies the repeated auctions in the state of Oklahoma.
Repeated Auctions in Oklahoma from November 1999 to March 2000	A dummy variable that identifies the repeated auctions in the state of Oklahoma between November 1999 and March 2000.
Repeated Auctions in Oklahoma after March 2000	A dummy variable that identifies the repeated auctions in the state of Oklahoma after March 2000.
Number of bidders	The number of bidders in an auction.
Log number of bidders	The logarithm of the number of bidders in an auction.
Expected number of bidders	The expected number of bidders is calculated using past information for each bidder and the plan holder list. For each bidder at time *t*, we take the past bidding to plan holder ratio. This gives a probability of bidding for each bidder. Then for an auction at time *t*, we sum across these participation probabilities for all plan holders in an auction.
Number of plan holders	Number of plan holders in an auction.

Log of engineer's estimate — The logarithm of the ECE for a given auction.

Capacity utilized — The utilization rate is the current project backlog of a firm divided by the maximum backlog of that firm during the sample period. For firms that have never won a contract, the utilization rate is set to zero. Data from the year 1997 are used to construct a set of initial starting value for the capacity utilization variable. The 1997 data is not used in the empirical models. The backlog variable is constructed as follows. For each project awarded, both the value of the contract and the length of the contract in days are given. We assume that a project is completed in a uniform fashion over the length of the contract. A contract backlog is constructed in each month by summing across the remaining value of *all* existing contracts in Texas and/or Oklahoma for a firm. So for both Texas and Oklahoma firms, the backlog includes all awarded projects in the states. As projects are completed, the backlog of a firm goes to zero unless new contracts are won.

Distance to the project location — The logarithm of the distance to a project is constructed as the distance between the county the project is located in and the distance to the county of the firm's location [log(distance+1)]. The county location is measured by the longitude and latitude at the centroid of the 'county seat.'

Average rivals winning to plan holder ratio — The measure of rivals' past average success (*ARWP*) in auctions is constructed as the average across rivals of the ratio of past wins to the past number of plans held. This variable incorporates two aspects of past rival bidding behavior. It incorporates both the probability of a rival bidding given they are a plan holder and the probability the rival wins an auction given that they bid. These probabilities are updated monthly using the complete set of bidding data in Texas and Oklahoma. The probabilities are initialized using data from 1997.

Closest rival's distance to the project location — This variable measures the distance (log of miles) between the project location and the closest rival.

Rivals minimum backlog — This variable contains the minimum the backlog of the rival firms in an auction [log(backlog+1)]. See the capacity utilization discussion above for a detailed explanation of how the backlog variable is constructed.

Seasonally unadjusted unemployment rate — The monthly state-level unemployment rate in Oklahoma and Texas from the US Bureau of Labor Statistics.

Three month average of the real volume of projects — This variable measures the three month moving average of the real volume of all projects for Oklahoma and Texas. The real volume of projects is constructed by adding the ECE across projects up for bid in a month for Oklahoma and Texas, respectively, and deflating the current value by the PPI. Then we divide it by the average of the real volume for each state to calculate the relative real volume.

Three month average of the number of building permits — This variable measures the three month moving average of the relative number of building permits for Oklahoma and Texas. The data come from the US Bureau of Economic Analysis.

Project type dummies	All projects are grouped into six main categories based on the description of the project. They are asphalt paving projects, clearance and bank protection projects, bridge projects, grading and draining projects, concrete work and traffic signals and lighting projects. The dummy on asphalt projects is the omitted group in the regressions.
Monthly dummies	Monthly dummies are set of 12 variables that control for the months of the year. The omitted month is January.
Project location dummies	ODOT has divided the state of OK into eight divisions. Similarly TXDOT has divided TX into 25 divisions. OK borders seven of these TX divisions. The project location dummies identify the 15 divisions from which we draw data for our analysis. OK division 1 is the omitted group in the Poisson regressions.

Note: All data come from the Oklahoma Department of Transportation and the Texas Department of Transportation except the state-level unemployment and building permits data that come from the Bureau of Labor Statistics and the Bureau of Economic Analysis, respectively.

Table B2: Summary Statistics of the Regression Variables

Variable	Mean	Standard Deviation
Relative value of bids	1.068	(.288)
Relative value of winning bids	.949	(.194)
Auctions specific standard deviation of relative bids	.133	(.130)
Auctions specific range of relative bids	.326	(.308)
Oklahoma bids	.501	(.500)
Bids from November 1999 to March 2000	.073	(.260)
Oklahoma bids from November 1999 to March 2000	.034	(.182)
Bids after March 2000	.620	(.485)
Oklahoma bids after March 2000	.308	(.462)
Repeated Auctions	.029	(.168)
Repeated auctions in Oklahoma from November 1999 to March 2000	.006	(.078)
Repeated auctions in Oklahoma after March 2000	.012	(.108)
Number of bidders	4.697	(2.171)
Log number of bidders	1.664	(.379)
Expected number of bidders	4.525	(2.203)
Number of plan holders	7.627	(3.747)
Log number of plan holders	2.063	(.434)
Capacity utilized	.238	(.272)
Distance to the project location	4.207	(1.581)
Average rivals winning to plan holder ratio	.149	(.054)
Closest rival's distance to the project location	2.871	(1.725)
Rivals minimum backlog	2.380	(5.146)
Seasonally unadjusted unemployment rate	4.621	(1.088)
Three month average of the real volume of projects	1.065	(.362)
Three month average of the number of building permits	1.019	(.157)
Asphalt projects	.298	(.456)
Erosion control projects	.009	(.094)
Bridge projects	.355	(.478)
Grading and drainage projects	.149	(.356)
Concrete projects	.044	(.204)
Traffic projects	.145	(.352)